

NDOT Research Report

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**Automated Pedestrian Detection, Count and
Analysis System**



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AUTOMATED PEDESTRIAN DETECTION, COUNT AND ANALYSIS SYSTEM

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This report is submitted to NDOT as part of the quarterly progress report for the project
“Automated Pedestrian Detection, Count and Analysis System” - Acct # 2331-254-789K

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AUTOMATED PEDESTRIAN DETECTION, COUNT AND ANALYSIS SYSTEM

1. TITLE

AUTOMATED PEDESTRIAN DETECTION, COUNT AND ANALYSIS SYSTEM

2. INVESTIGATORS

Venki Muthukumar, Brendan Morris, Emma Regentova, Alex Paz and Erin Breen

3. PI's, STUDENTS AND RESPONSIBILITIES

| FACULTY/TEAM | STUDENT | TASK |
|------------------|---|--|
| Venki MUTHUKUMAR | Min Lan (MS) Matthew Parker (UG) Jordan Mulcahey (UG) | Pedestrian Count and Tracking System Vehicle Counting and Tracking System Pedestrian-Vehicle Conflict System |
| Emma REGENTOVA | Farideh Foroozandeh Shahraki (MS) | Bicycle Detection and Tracking System |
| Brendan MORRIS | Mohammad Shirazi (PhD) | Pedestrian-Vehicle Conflict System |

4. PROBLEM DESCRIPTION:

Pedestrian and bicycle count data is necessary for transportation planning, implementing safety countermeasures, and traffic management. This data is critical when evaluating the pedestrian level of service of safety (LOSS) and pedestrian safety performance function (SPF). Also, a performance analysis tool with both vehicle and pedestrian data is required to comprehensively analyze intersection safety.

The goals of this project are to:

- i. Develop a pedestrian-bicycle count automated system.
- ii. Develop a pedestrian-vehicle conflict detection system.
- iii. Collect data of pedestrians, bicycles and pedestrian-vehicle conflicts.
- iv. Develop a database and analysis tools based FHWA recommended safety tools to do analysis and visualization of data to select and evaluate pedestrian-bicycle safety countermeasures.

5. RESEARCH TASKS

The primary goal of the proposed research is to develop an automated system/framework that detects and counts pedestrians, generates pedestrian flow characteristics, and evaluates pedestrian-vehicle conflicts for a given pedestrian crossing to improve safety. The proposed research will also develop a database system for safety analysis tool to perform network screening and countermeasure selection.

modules. The database will include typical intersection analysis data plus pedestrian and bicycle counts and conflict data.

The detailed research tasks are presented below:

Task 1: Literature Review

The literature review task is sub-divided into three sub-tasks:

Task 1.1 – Literature survey of pedestrian counting systems,

Task 1.2 – Literature survey of pedestrian-vehicle conflicts, and

Task 1.3 – Literature survey of pedestrian safety database, analysis tools, and countermeasure selection.

Deliverables: Literature review report summarizing the state of the art pedestrian and bicycle detection and count technologies, current practice employed by various entities for pedestrian and bicycle counts, capabilities and drawbacks of various pedestrian and bicycle data analysis tools, databases and safety countermeasure selection tools.

Task 2: Pedestrian-Bicycle Count System

The software will be able to process live video feeds, extracting pedestrian and bicycle counts along with the direction of motion, pedestrian motion paths, speed of walking, and vehicle counts along with directions, by lane. The extracted data is stored in a simple flat database along with the time stamp. The performance of the pedestrian-bicycle count tool will be evaluated and summarized.

Deliverables: A working software system running on multi-core GPU system that will be able to count and extract pedestrian and bicycle flow characteristics with minimal configuration by the user. A detail documentation of system setup, use of existing intersection cameras, system setup parameters, and extracted data will be submitted to NDOT.

Task 3: Pedestrian-Vehicle Conflict Detection System

The software will be able to process live video feed and detect pedestrian-vehicle conflicts. The extracted data is stored in a simple flat database along with the time stamp. The performance of the pedestrian-vehicle conflicts detection tool will be evaluated and summarized.

Deliverables: A working software system running on multi-core GPU system that will be able to extract pedestrian-vehicle conflicts with minimal configuration by the user. A detail documentation of system setup, system setup parameters, and extracted data will be submitted to NDOT.

Task 4: Development of Pedestrian Safety Database and Analysis Tool

After extraction of the pedestrian and vehicle count data and conflict data from live video feeds, the data is imported into a safety database using a custom database. The analysis tool will also be capable of classification and grouping of intersections with similar pedestrian-bicycle safety characteristics. The analysis tool will utilize the crash and conflict data in conjunction to screen the network for critical pedestrian locations to determine different levels of services (LOS) and safety metrics.

Deliverables: The research team will deliver a database populated with data extracted from the above Tasks 2 and 3 and provide a software tool for comprehensive intersection safety analysis and visualization tools. The software tools will identify safety countermeasures based on the data analysis.

Task 5: Final Reporting

A detailed report, user guide, and large-scale deployment instructions for pedestrian-bicycle count and conflict hardware and software system will be provided as technology transfer document.

Deliverables: The final report, presentation and demo including all findings from the project tasks along with code and software required for the pedestrian safety program.

6. PROJECT SCHEDULE

The proposed start date for the project is Jan. 1, 2015 and is expected to be completed by Dec 31st 2015. The schedule for the tasks with their respective duration in months, milestones, and reports are shown below. Quarterly task group meetings will be held with the NDOT Champions and Consortium of Advisors* involved in the project during the first week of every quarter to discuss project progress and issues. The documentation is the first quarterly report of this project.

Table 1: Project Timeline

| TASK NAME | MONTH | | | | | | | | | | | |
|--|-------|---|--------|--------------------------|---|---|---|-----|-------------|----|----|----|
| | 1 | 2 | 3 | 4❖ | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| TASK 1 - Literature Surveys | | | ★ ○ | | | | | | | | | |
| TASK 2 - Pedestrian-bicycle Count System | | | | ○ | | ○ | | | | | | |
| TASK 3 - Pedestrian-vehicle conflict System | | | | | ○ | | | ○ | | | | |
| TASK 4 - Database, Analysis & Countermeasure | | | | | | | ○ | | | | ○ | |
| TASK 5 - Final Reporting | | | ★ | | | ★ | | | ★ | | | ○ |
| ○ → Milestones | | | ★ → | Interim Reports/Meetings | | | | ❖ → | We are here | | | |

7. SUMMARY OF PROGRESS

This section summaries the project progress from Jan 1st 2015 till March 31st 2015. Three graduate and two undergraduate students have been working on the project till date. One PhD student, Mr. Mohammad Shirazi is working on pedestrian-vehicle conflict detection under the supervision of Dr. Brendan Morris. Ms. Farideh Foroozandeh Shahraki (MS students) is working on bicycle detection and tracking under the supervision of Dr. Emma Regentova. One MS student, Mr. Min Lan and two undergraduate student (Mr. Matthew Parker and Mr. Jordan Mulcahey) are working on pedestrian, vehicle and parallel implementation in CUDA respectively. We are in the process of collecting data at specific intersections to evaluate the detection and tracking algorithms. Also, testing of safety analysis tools like PBCAT, LOS+ and HSIS. We are waiting for ARGIS related data from NDOT to evaluate existing safety analysis tools. Literature review of detection and tracking methods of pedestrians, bicycles, and vehicles and safety indices/metrics or conflict indicators to determine the pedestrian-vehicle conflicts have been completed. During the next quarter we will implement the identified methods to extract data from the video frames.

8. LITERATURE REVIEW

There exists a great deal of literature on general people detection and tracking (not pertaining to crosswalks) for applications like surveillance, motion analysis, recognition, etc [8.1-1,2,3,4]. Similarly vehicle detection and tracking have been extensively studied for transportation related research and

applications. However, there exists few research works on detection of pedestrian-vehicle conflicts [8.1-5,6,7] and there exists no work on automated detection of pedestrian-vehicle conflicts. This section briefly outlines past research work on pedestrian and vehicle detection, tracking, pedestrian counting and pedestrian-vehicle conflict at crosswalks.

8.1 Pedestrian Detection and Tracking:

Pedestrian detection and tracking algorithms can be classified based on the following criteria: location of the camera - in-vehicle and pedestrian behavior analysis; number of cameras - monocular and stereo-cameras; detection approaches - Holistic, Part-based, Patch-based, and Motion-based detection [8.1-34]. Many pedestrian detection algorithms have been implemented for mainly in-vehicle applications, like pedestrian driving assistance systems. Earlier researchers have employed the following methods for pedestrian detection and tracking: 1) Pedestrians tracking as blobs [8.1-8,9], 2) Pedestrians tracking based on contours and shapes [8.1-10,11] and 3) Pedestrian body modeling and template matching [8.1-12].

One of the most effective algorithms for pedestrian detection is the sliding window based approach. Papageorgiou et al. [8.1-13] proposed one of the first sliding window detectors, applying support vector machines (SVM) classification over the extracted features using Haar wavelets. Viola and Jones [8.1-14] accelerated the above process constructing cascade classification structures for efficient detection, and utilizing AdaBoost for automatic feature selection. Dalal and Triggs [8.1-15] popularized histogram of oriented gradient (HOG) features for detection. Shape features are also a frequent cue for detection that include characteristics such as edges, shape, and pose. Wu and Nevatia [8.1-16] utilized a large pool of short line and curve segments, called 'edgelet' features, to represent shape locally. Similarly, 'shapelets' [8.1-17] are shape descriptors Bourdev and Malik [8.1-18] proposed to learn an exhaustive dictionary of 'poselets': parts clustered jointly in appearance and pose.

Researchers have also combined characteristics of motion with structural feature extraction techniques. Wojek and Schiele [8.1-19] proposed a multi-feature technique that is a combination of Haar-like features, shapelets [8.1-17], shape context [8.1-20] and HOG features outperforms any individual feature. Walk et al. [8.1-21] extended this framework by combining the motion features with the above listed multi-features. Doll'ar et al. [8.1-22] proposed an extension of Viola and Jones where Haar-like feature are computed over multiple channels of visual data. 'Fastest Pedestrian Detector in the West' [FPDW] [8.1-23], this approach was extended to fast multi-scale detection after it was demonstrated how feature computed at a single scale can be used to approximate feature at nearby scales. Performance evaluation of existing approaches suggests that the above method provides the maximum processing speed (fps) to minimum miss rates.

This section lists the research conducted specifically for pedestrian detection to extract pedestrian behaviors. Pedestrian detection and tracking methods have been employed to derive both macroscopic and microscopic pedestrian flow data. Most transportation related works, extract this data using manual collection techniques. Only a hand full of researches has employed video-image processing techniques for automated pedestrian data collection. This is due to the fact that video-image processing of pedestrians and their behavior at crosswalks require complex modeling and video-image processing

algorithms. Macroscopic pedestrian data collection includes fundamental pedestrian flow characteristics like volume, speed and density. Microscopic pedestrian data flow includes inter-pedestrian behaviors, pedestrian interaction with their environments, individual speed and individual behavior. Yasutomi et. al. [8.1-24] and Mori et. al. [8.1-25] employed pedestrian detection and tracking using the motion model of the pedestrians. Yasutomi et. al. [8.1-24] determines the state of a moving pedestrian, such as position and velocity, by estimating the kinematic model, a measurement model and a tracking filter. Mori. at. al [8.1-25] proposed a fast tracking algorithm to track the movement of many individual vehicles or pedestrians. Sullivan et. al [8.1-26] developed a pedestrian detection and tracking approach based on shape representation of the pedestrians using an active deformable model. Ismaeil et. al [8.1-27] presented a pedestrian motion estimation technique for the coding of video sequences that is based on long-term temporal prediction. The motion vector of a moving object is tracked from one frame to another using a projection method. The motion estimation algorithm used is based on an optimum fast block-matching algorithm. Haritaoglu et. al. [8.1-28] proposed detection and tracking of pedestrian activities outdoor using silhouettes (outlines). Oren et. al. [8.1-29] pedestrian detection technique employs wavelet transforms to classify pedestrians from the scene. Pedestrian detection and tracking approach based on color segmentation to differentiate pedestrians from the background was adopted by Gover et. al [8.1-30] and Heisele et.al [8.1-31]. Onoguchi et. al [8.1-32] proposed a two camera system to estimate the pedestrian based on size, shape and location using projection techniques and Kanatani transforms. Stauffer et. al [8.1-33] proposed an event detection and activity classification of the pedestrians for side view cameras.

8.2 Pedestrian Data Collection Studies:

Robert J. Schneider [8.2-1] study presents a methodology for estimating weekly pedestrian intersection crossing volumes based on 2-h manual counts. Results of this study demonstrate how pedestrian volumes can be routinely integrated into transportation safety and planning projects. He also created a simple pilot model of pedestrian intersection crossing volumes. H. Joon Park et. al. [8.2-2] identify the need for and recommend a guideline for dynamic pedestrian walking speeds during pedestrian clearance intervals that fluctuated on the basis of how pedestrians behaved in crosswalks with various pedestrian densities. Mohamed H. Zaki et. al. [8.2-3] presents the use of a set of CV techniques for the automated collection of cyclist data. Cyclist tracks obtained from video analysis were used to perform screen line counts as well as cyclist speed measurements. Further analysis was conducted on the mean speed of cyclists with regard to several factors (e.g., travel path, helmet use, group size). John N. Ivan et. al. [8.2-4], reported experiences with implementing various methods of influencing vehicle speeds, including automated enforcement, self-explaining roads, and in-vehicle systems, are presented and discussed. Tarek Sayed et. al. [8.2-5] successfully automating conflict detection with data extracted from video sensors on right-turn safety improvement was implemented at an intersection. The video data were analyzed and traffic conflicts were measured with an automated traffic safety tool. Distributions of the calculated conflict indicators before and after the treatment showed a considerable reduction in the frequency and severity of traffic conflicts. Simon Li et. al. [8.2-6] used computer vision techniques for automated collection of pedestrian data through several applications, including

measurement of pedestrian counts, tracking, and walking speeds. Manual counts and tracking were performed to validate the results of the automated data collection. The results show a 5% average error in counting, which is considered reliable.

8.3 Vehicle Detection and Tracking:

Vehicle tracking, which is defined as finding the location of a vehicle in the scene on each frame of the sequence, when processing a video sequence of the road. Traffic measurements like vehicle speed, vehicle length, average vehicle speed, volume etc. that are considered to be vital can be obtained by tracking a vehicle.

The earlier popular vehicle detector consists of a wire loop installed below the roadway and an electronic oscillator that drives electrical energy through it. Whenever a vehicle passes over the loop, there is a change in the magnetic inductance of the loop causing an increase in the frequency of the electronic oscillator. Demerits of the above method include being expensive, inconvenient installation, unreliable over the time visual surveillance incapability, etc.

Detection through video-image processing is one of the most attractive alternative new technologies, as it offers opportunities for performing substantially more complex tasks than Loop detectors. It gained lot of importance from researchers due to its efficiency, inexpensive installation, etc. Also vehicle tracking using video-image processing, can yield traditional and behavioral traffic parameters such as flow and velocity, as well as new parameters such as lane changes and vehicle trajectories.

In general, vehicle detection can be implemented in 2 types: 1) means of active sensors and 2) passive sensors. Loop Detectors, Lasers, Lidar, Millimeter-Wave Radar are examples of active sensors and video cameras act as passive sensors. The accuracy of detection is dependent on parameters like occlusion, day/night traffic conditions, noise associated with camera, etc. Numerous algorithms have been proposed to detect vehicles in the frames captured by video cameras efficiently. Algorithms employed for vehicle tracking can be classified as

- a) Region based
- b) Active Contour based
- c) Feature based
- d) Optical Flow based
- e) Model based (2D and 3D Models)

The efficiency of an algorithm varies with parameters like day/night traffic, climatic conditions, occlusion, etc.

In the region-based approach connected regions in the image are determined and a 'blob' is associated with each vehicle. These blobs are tracked over time using a cross-correlation measure. Typically, the process is initialized by the background subtraction technique. A Kalman filter-based adaptive background modeling [8.3-1,2] allows the background estimate. Foreground objects (vehicles) are detected by subtracting the incoming image from the current background estimate, looking for pixels where this difference image is above some threshold and then finding connected components. This approach works fairly well in free-flowing traffic. However, under congested traffic conditions, vehicles partially occlude instead of being spatially isolated, which makes the task of segmenting

individual vehicles difficult. Such vehicles will become grouped together as one large blob in the foreground image.

In the active Contour Based Tracking the basic idea is to have a representation of the bounding contour of the object and keep dynamically updating it. The previous system for vehicle tracking developed Koller, et al [8.3-3,4], was based on this approach. The advantage of having a contour based representation instead of a region-based representation is reduced computational complexity.

An alternative approach to track vehicles employs extracting and tracking sub-features such as distinguishable points or lines (i.e. as salient features of the object). The advantage of this approach is that even in the presence of partial occlusion, some of the features of the moving object remain visible. While detecting and tracking vehicle features makes the system more robust to partial occlusion, a vehicle will have multiple features. However, the inability to detect vehicles that are partially occluded persists.

Optical Flow based approach uses the pixel intensity values in RGB, YUV, and other color systems to detect a vehicle. In one such algorithm, the Histogram of a frame defines the intensity distribution of the frame and the differences of histograms between the frames are considered to detect a vehicle. Other methods use the edges of the objects found on the frame and their relative displacements to detect a moving object. The edge detection can be done using different filters like Canny, Sobel, Robert, etc. The efficiency of detection relies on the ability of the filter to cope with different light conditions, camera resolution, motion blur and the complexity of the scene. Some approaches employ the processing of a particular area through the consecutive frames.

Model based vehicle tracking methods are based on matching a model in the image plane to each observed vehicle. The model is based on the characteristic edges of an intensity image of a vehicle. This model is applied to track vehicles through image sequences. The object recognition process is initialized by formulating a model hypothesis using a reference model and initial values provided by motion segmentation step from a model-based tracking [8.3-5,6].

Vehicle tracking commercial systems are known as "fourth generation" VIPS, include AUTOSCOPE [8.3-7], CMS Mobilizer [8.3-8], Autocolor [8.3-9,10] and RoadWatch [8.3-11].

8.4 Bicycle Detection and Tracking:

Introduction

The number of entire traffic accidents is currently decreasing because of the influence of many safety technologies in the automobile. But the rate of bicycle's accident to the entire traffic accidents is gradually increasing. On the other hand, an advanced safety vehicle system is working on a plan to decrease traffic accidents. To prevent traffic accidents, it is necessary to detect the risk of traffic accidents (a human, a car, a bicycle, etc.)[8.4-9]. Therefore, bicycle detection in video surveillance system is of great significance to the research and application of Intelligent Transportation Systems (ITS) to decrease traffic accidents. For bicycle detection, there is wide variety of detection technologies. Applications that have been developed for bicycle detection are inductive loops, microwave sensors, infrared sensors and vision-based optical cameras. All of these methods except vision-based optical

cameras do not have distinctive profiles for bicycles and pedestrians or bicycle and motorcycle. But in vision-based technology, cameras are used which are inexpensive and abundant and are relatively easy to use, but they are useful as detection and counting systems only when accompanied by efficient algorithms that analyze the images and recognize bicycle [8.4-1]. In what follows, we analyze required component and properties that characterize bicycle or related to that properties of the system which are to be taken into account for the method development. Then, we analyze existing methods specially designed for bicycle detection. And At the end, we mention what we are going to pursue for bicycle detection.

Properties and requirements of the bicycle detection system

The Physical Properties of Bicycles: Bicycles are made up of three distinctly identifiable objects that could be used separately or in combination to identify an object in an image as a bicycle.

1. The rider: Much work has been done to identify humans in images.
2. The frame: Frames are not used for bicycle detection because nearly endless numbers of distinct frame configurations are available, and it would be troublesome to consider just one of them as a template for a bicycle because detecting other configurations would be difficult or maybe impossible.
3. The wheels: The wheel set is composed of two rims of equal size and tires encircling the rims at the outside edge. Bicycles generally have one of two possible standardized wheel sizes. Mountain bicycles are typically built with a standard 26-inch diameter rim size and road bicycles are built with a 700c rim size (approximately 29 inches)[8.4-3]. Because wheel sizes and shapes are standard, wheels are efficient items in bicycle detection. They almost have a distinct template.

Bicycle paths - Three categories of bicycle paths [8.4-3]:

1. For the exclusive use of bicycles
2. For a mixed use of bicycles and pedestrians
3. Demarcated at the side of streets and highways

Size, Speed considerations for bicycle detection system

1. Differences between pedestrian and bicycle that should be considered for bicycle detection
 - a. Bicycle + person on the bicycle are larger than a pedestrian or larger than a wheelchair man
 - b. The speed of a bicycle is more than that of a pedestrian
2. Differences between vehicle and bicycle that should be considered for bicycle detection
 - a. Bicycle is smaller than vehicle and motorcycle
 - b. The speed of a bicycle is lesser than that of a vehicle

Constraints

There are some constraints associated with bicycle detection:

1. The video quality is low and differentiates between pedestrian and bicycle can be difficult, moreover, detecting bicycle based on its wheels or moving legs is troublesome.

2. Bicycle's appearance, shape and motion can change dramatically between viewpoints and a person riding on the bicycle is a non-rigid object.
3. Real time environment can be very complex, so separating background from foreground can be complex problem
4. If bicycles move close to vehicle, detecting bicycle in street will be complex.
5. There are a large variety of bicycle models, and methods which train classifier for a specific model not necessarily work for other models.
6. In bicycle lane, it could be that bicycles move together in groups (clutter and occlusions).
7. After analyzing characteristics of bicycle that should be considered for bicycle detection, we discuss existing bicycle detection methods. First we categorize detection methods into four groups, then put each existing technique in one of these groups and argue about them.

Vision- based detection Methods

In this part, vision based detection methods are categorized into four groups.

1. Feature-based methods
2. Shape-based approaches (variant under viewpoint)
3. Color-based approaches (constant under view point)
4. Texture-based approaches
5. Template-based methods
6. Fixed template matching (object do not change with respect to the viewing angel of camera)
7. Deformable template matching (object change with respect to the viewing angel of camera)
8. Motion-based methods
9. Combination model (motion-based method with feature-based method or template-based method)

Feature-based methods:

Vision-Based Bicycle Detection Using Multi-scale Block Local Binary Pattern [8.4-7]

Because of low speed, low occupancy, pace, and flexibility of bicycle travelling, cyclists often move together in groups. This method proposes a real-time multiple bicycle detection, which could provide real-time bicycle's traffic information (the volume, the velocity, etc.) for traffic control and management. In this method, an effective feature called Multi-scale Block Local Binary Pattern (MBLBP) is provided for bicycle feature representation. MBLBP is a texture-based feature descriptor. It is in fact the basic Local Binary Pattern (LBP), but compared to basic LBP, it can capture large-scale structures that may be the dominant features of images. In next step, a cascade classifier with 50 stages trained by AdaBoost algorithm is proposed in this method to obtain possible bicycle candidates. A two-layer detection strategy is operated in this paper to reduce the false positive detections.

Constraints of this method:

There is no mention of problems related to the discrimination bicycle from motorcycles.

Advantages of this method:

1. It is a good method for detecting bicycles that move together in a group or bicycles that move close to vehicles.
2. It can find typical bicycles with different size, pose and bicyclist's clothing.

3. Negative samples for the cascade of classifiers are chosen really precisely to reduce false alarm.
4. Work on very low quality video frames.

Template-based methods:

A hybrid Hough-Hausdorff method for recognizing bicycles in natural scenes [8.4-3]

In this method, the authors propose an approach that utilizes the Hough transform and the Hausdorff distance in a hybrid algorithm. The Hough Transform is initially used to find possible bicycle wheels in the imagery. The locations near these potential wheels are then analyzed using the Hausdorff distance to determine if a strong match exists with the bicycle model. This method is effective since the Hough enforces a strong geometric constraint that excludes image artifacts that cause the Hausdorff to report false positives. In turn, the Hausdorff can verify the existence of a bicycle even when the Hough finds only one of the two wheels. [8.4-3]

The Hough transform is used to find edge elements that conform to known geometric shapes such as lines, circles, ellipses, and other simple curves, with detection performed through use of the parametric equations that describe the particular shape. Because bicycles contain derivations of simple geometric shapes such as somewhat predictable line configurations (the frame) and circles (i.e., the tires and wheels when viewed from the side) this approach has merit for the problem of detecting bicycles [8.4-3]. Then, the authors use Hausdorff distance to measure similarity between data collected from Hough transform and the data contained in a template and provide reasonable results for bicycle detection.

Constraints of this method:

1. Bicycles are viewed from the side of a bicycle lane
2. The authors make no mention of problems related to the discrimination bicycle from motorcycles.
3. This method has not considered bicycle variety and just focus on a simple bicycle model

Deformable part model and an EKF algorithm [8.4-4]

In this paper, the authors built a three-component bicycle model using Felzenszwalb's part-based model [8.4-5]. This model is trained via a SVM to detect bicycle under a variety of circumstances. The features that are used in this paper are PCA (Principal Component Analysis) version of HOG features. Firstly, each block-based feature of the image is encoded using HOG, then PCA is used to reduce the dimensions of the HOG feature set, and in this method ,13-dimensional feature set obtained by performing PCA can capture same information like original 36-dimensional feature set.

Advantages of this method:

1. Consider more than one viewpoint of bicycle (i.e., frontal, 45 degree, side view).
2. Has more precision that one or two component bicycle model.
3. Speed improvement for detection process (using PCA).

Constraints of this method:

Using part-based model in detection of bicycle in low quality frames can be more difficult than single template approach

Applying HOG feature to the detection and tracking of a human on a bicycle [8.4-9]

In this method, a HOG model of bicycles are defined and trained via a Real Adaboost to detect bicycles under various circumstances. This method also detects bicycle's driving direction, and the reason for detecting bicycle's driving direction is to predict a bicycle coming suddenly into a driver's sight. For detecting driving directions, three detectors are used. By using mean shift clustering and the nearest neighbor algorithm, three detected windows merge.

Advantages of this method:

Detecting bicycle's driving direction that can be useful to detect the risk of traffic accident.

Constraints of this method:

Variation in the human form and position are extremely diverse, especially in cycling domains. So, detecting bicycle based on the bicyclist can be complex.

Bicycle detection using pedaling movement by Spatiotemporal Gabor Filtering [8.4-6]

This paper includes shape-based object detection using HOG and SVM and relative motion detection for leg movements in bicycle pedaling. The leg movement, which can be achieved by using spatiotemporal 3D Gabor filtering, can discriminate bicycles from similar objects such as motorbikes. First, detecting moving object by motion detection methods, and then determining it's a bicycle or not (based on shape, velocity and leg movement).

Advantages of this method:

Discriminates between bicycle and motorcycle.

Constraints of this method:

Detecting bicycle based on its wheel movement and leg movement on pedal can be troublesome from low quality video frames.

Vision-based bicycle/motorcycle classification [8.4-2]

This method presents a feature-based bicycle recognition algorithm. The algorithm extracts some visual projective features focusing on the wheel regions of the targets. And then support vector machine (SVM) is applied to distinguish bicycles from motorcycles in real-world traffic scenes. The functionalities provided by this method are: vehicle detection, counting, classification, average speed estimation, and compilation of the turning movement table for each monitored intersection. Vehicle classes recognized by the system are: bicycle, motorcycle, car, van, lorry, urban bus and extra urban bus [8.4-2].

Constraints of this method:

1. Focused on wheel region in bicycle detection. It is an appropriate method in high resolution video, and not precise enough to detect bicycle and motorcycle in red light camera videos that are poor in quality.
2. This method has not used a dynamic background pixel in the part of motion detection.

Advantages of this method:

1. Implementing a classifier to detect bicycle from motorcycle.

2. Uses a motion-based classifier to distinguish bicycle and motorcycle from other moving objects like pedestrian, vehicle, and then uses feature based classifier to differentiate between bicycle and motorcycle.

A method for bicycle detection using Ellipse Approximation [8.4-8]

This method is a combination of motion detection and shape-based feature detection and it has two steps. First step is estimating the moving object region based on inter-frame differences and optical flow, and then uses an approximate ellipse in the region of the moving object to detect tire of the bicycle. In this method, by using a floating threshold value, the shape of tires is obtained and an arc of a tire is extracted by performing thinning. The tire position is estimated by approximating the extracted arcs, and if this algorithm is able to estimate a portion of a tire, then the moving object is detected as a bicycle.

Constraints of this method:

1. This method is appropriate just for side view and 45° view of bicycle, but not for front or rear views.
2. Focuses on wheel region of object which is an appropriate method in high resolution video, and it is not accurate enough to detect bicycle and motorcycle in red light camera videos which are poor in quality.
3. Cannot differentiate between bicycle and motorcycle.
4. It cannot detect the direction of a bicycle, so cannot predict that bicycle is coming into a driver's sight or not.

Conclusions

In this survey, we have reviewed the bicycle detection reported in recent years. Bicycle detection can be divided into feature-based, template-based, a combination of feature-based and motion-based or template-based and motion-based methods. At last, we discuss the existing methods in bicycle detection, and compare them in a table. Based on this comparison, we can state that most of detection methods are template-based or combination methods. We will pursue first HOG feature descriptor and SVM classifier as they have displayed the best performance. Also, we will look at tracking methods. Finally, we will look at fast (real-time) implementation of the methods. At last, we will evaluate the conflict cases such as bicycle- pedestrian and bicycle-car scenarios.

TABLE I: Comparison of Bicycle Detection Methods

| | Feature-based | Template-based | | | Combination method | | |
|--|----------------------------------|-----------------------|---------------------|--|---------------------------|---------------------------------|--------------------------------------|
| | [8.4-7] | [8.4-3] | [8.4-4] | [8.4-9] | [8.4-6] | [8.4-2] | [8.4-8] |
| High/Low Res. video | Low | Low | Low | Low | High | Low | High |
| Image/video | Video | Image | Video | Video frames | Video | Video 288×352 | Video frames 1095×821 |
| View | Front Rear Side | Side | Front 45 Side | Front Left Right | Side | Front rear side | Side 45 |
| Feature descriptor | MBLBP | Hough Transform | HOG-PCA | HOG | HOG | | Optical flow |
| Classifier | Cascade AdaBoost | Hausdorff distance | SVM | RealAdaboost | SVM | Non-linear SVM | |
| Real-world traffic scenes | Y | Y | Y | Y | Y | Y | N |
| Distinguish bicycle form motorcycle | N | N | N | N | Y | Y | N |
| Focus | Whole | Wheel | Whole | Whole | Whole | Wheel | Wheel |
| Speed | 10 fps | Good | Fast | Good | Good | 25 fps | Good |
| Test (# of samples) | 300 + 300 - | 25 | 517 + 3300 - | 4000 + 6000 - 349 | 50 bicycle 50 human | 45 bicycle 144 motorcycle | 30 frames |
| Accuracy | Improved by 2 layer detection | 96% in detection | 87% in detection | 89.9% in detection 93.5 % in driving direction | 76% | 96.7% | 30% - UD 68% - FD 3% - correct |

8.5 Safety Analysis Metrics and Conflict Indicators at Intersections

INTRODUCTION

Intersections are well-known targets for monitoring because of the high number of reported accidents and collisions. Around two million accidents and 6,700 fatalities in the United States occur at intersections [8.5-1], constituting 26% of all collisions [8.5-2]. Moreover, one fourth of all fatal accidents happen near intersections [8.5-2]. As a consequence, accident avoidance and safety improvement is a prime focus being addressed by advanced driver assistance and safety systems. Safety analysis is fundamental element used for boosting safety and preventing accidents at intersections. Safety analysis involves models and predictions of conflicts (i.e., close to the accident) and accidents that are built from the safety measurements or crash data sets and police reports. Conflict-based safety analysis techniques use surrogate safety measurements since real accident data is difficult to assess due to the lack of good predictive models of accident potentials and lack of consensus on what constitutes a safe or unsafe facility. As result, surrogate safety measures are introduced and validated in numerous studies to address safety issues [8.5-3][8.5-4].

CONFLICT-BASED SAFETY ANALYSIS

A traffic conflict is mostly used in safety analysis is defined by Amundsen and Hyden [8.5-5] as: "An observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remained unchanged" [8.5-5].

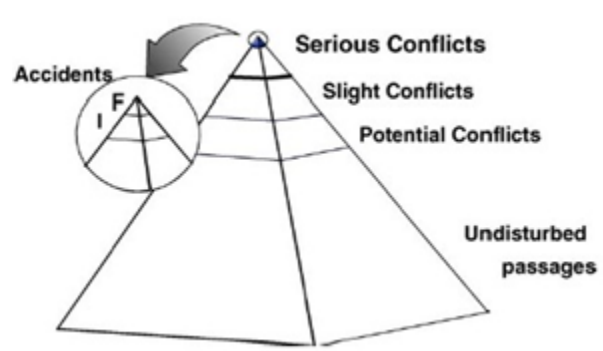


Fig. 1: Traffic safety pyramid measurement showing the hierarchy of traffic events (F= Fatal, I=Injury) [8.5-4]

Fig. 1 shows a hierarchical concept of using conflicts that imply critical observations used in safety analysis. An associated severity can be estimated for each traffic event in the hierarchy; thus, the severity represents its location in the hierarchy. As long as there is correlation between accidents and conflict-based safety measurements and the safety measurements are reliable and consistent in definition, they can be proven as practical metrics for safety analysis [8.5-3].

TABLE II shows some important safety measurements used in intersection studies for analysis of actual accidents. Fig. 2 shows the conflict line in a conflict point diagram as well as terms used in measuring surrogate safety. Time t_1 is the time of vehicle A starts encroachment by turning left and vehicle B takes brake to avoid collision at time t_2 . TTC and PET are shown as difference to reach the same point (reference point) in the area. TTC is calculated for the predicted arrival time and PET is calculated after

Vehicle B breaks and reaches the reference point. Low TTC and PET values imply a high probability of collisions.

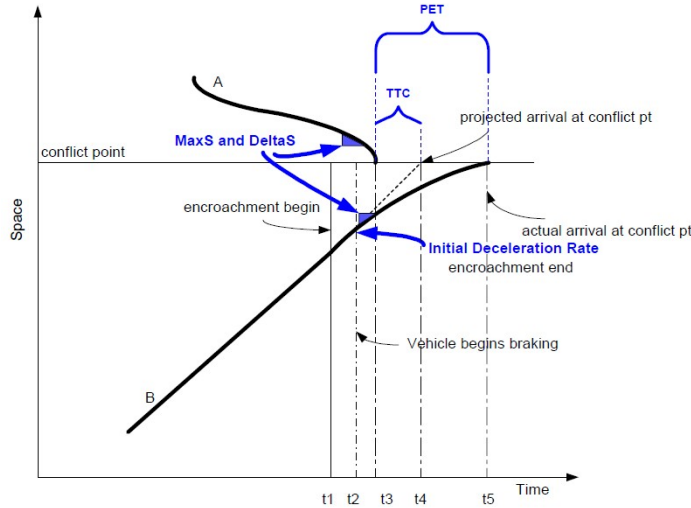


Fig. 2: Surrogates identified on a conflict point diagram [8.5-8]

The low TTC also can be mapped to a severity index with the following formula.

$$SI = e^{-\left(\frac{TTC^2}{2PRT^2}\right)}$$

Where SI is the severity index, ranging from 0 to 1, and PRT can be considered to be 2.5 s. The distribution of the severity index is an important measurement for safety evaluation [8.5-6]. In addition, Fig. 2 depicts $MaxS$ and $DeltaS$ which are defined as the maximum of speeds and relative speed of two vehicles, respectively.

Headway is another safety indicator in a car-following model [8.5-7]. Time headway is measured as difference of time that leading vehicle i and following vehicle $i-1$ reach a same location in car-following model.

$$H = t_i - t_{i-1}$$

TTC can also be written as fraction of time gap as below that l_i is length of vehicle i .

$$TTC_i = \frac{X_{i-1}(t) - X_i(t) - l_i}{V_i(t) - V_i(t-1)} = \frac{V_i(t)}{V_i(t) - V_i(t-1)} \times \hat{H}$$

$$\hat{H} = H - \frac{l_{i-1}}{V_i} = gap$$

TTC in car following model is defined when $V_i(t)$ higher than $V_i(t-1)$. Otherwise, a vehicle can have large or infinite TTC value but still relative small headway. This is major reason that headway is more appropriate. As result when TTC is high but headway is small, there is potential danger in car following model. Since availability and quality problems are associated with collision data, some studies have relied upon traffic conflict analysis as an alternative or a complementary approach to

analyze traffic safety. Traffic safety analysis has been investigated separately for each interaction type namely vehicle- vehicle and vehicle- pedestrian conflicts. TABLE III shows the representative works for conflict-based analysis regarding to each interaction type.

TABLE II: Safety measurements used at intersection studies

| Parameter | Definition |
|--------------------------------|---|
| Time To Collision (TTC) | The time for two vehicles (or a vehicle and pedestrian) to collide if they continue at their present speeds on their paths [8.5-9] [10] [11] [12] [13] [6]. |
| Distance To Intersection (DTI) | The distance until a vehicle reaches to stop bar with current speed. Stop bar is used as reference point [8.5-12], [13] [14] [15] [16] [17] [18] [19] [20] [11] [21]. |
| Time To Intersection (TTI) | The time remains until a vehicle reaches the stop bar with its current speed. Stop bar is used as a reference point [8.5-10] [16] [17] [18] [14] [19] [20]. |
| Time Headway | Elapsed time between the front of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point [8.5-9] [22] [23]. |
| Post-Encroachment Time (PET) | Time lapse between end of encroachment of a turning vehicle and the time that the through vehicle (or pedestrian) actually arrives at the potential point of collision [8.5-11] [12] [13] [6] [24]. |

For vehicle-vehicle conflicts, safety measurements include DTI [8.5-10], [8.5-21], [8.5-25] Headway [8.5-23], TTC, and TTC conflict indicators [8.5-11]. Besides calculating DTI and TTC, some studies have investigated signal violations [8.5-10], [8.5-25].

For vehicle-pedestrian conflicts, violations by pedestrians and their conflict with right- or left-turning vehicles mostly are studied. For example, Ismail et al. extracted DTI, PET, and TTC [8.5-12], [8.5-13]; and Zaki et al. [8.5-26] investigated pedestrian violations by comparing a given track and normal movement prototypes. Sayed et al. [8.5-6] relied on the development of a database to cover all interactions between road users, including TTC and other measurements. Since left-turn conflicts with pedestrians frequently occur, some studies addressed that issue by extracting vehicle speed and PET [8.5-24] or by using regression models to find the greatest contributing factors [8.5-27].

ACCIDENT-BASED SAFETY ANALYSIS

Accident-based safety analysis includes various methods used to learn and model accident patterns as well as making the prediction to prevent accidents. Numerous studies discussed various ways to address accidents for vehicle-vehicle and vehicle-pedestrian types as they are shown in TABLE IV.

For vehicle-vehicle accidents, vision-based methods are available that can address accidents and collisions based on predicting the future state of the vehicle, using vehicle dynamics. Collisions are detected if there is an overlap between the predicted 3D cubic models of vehicles at same time. As a typical example of vision-based work, Kamijo et al. [8.5-31] addressed three types of accidents 1) a bumping accidents, 2) stop and start in tandem, and 3) passing. These types of collisions were detected by using HMM to learn the crash patterns. Akoz [8.5-32] used continuous HMM for clustering paths, and linear regression for recognizing the severity of an accident.

Extracting features from tracking like the variation rate of velocity, position, area, and direction are quite common to make predictions on traffic accidents [8.5-33]. For example, Atev et al. [8.5-34], [8.5-35] inferred all possible pairs of rectangles that intersect in current and future time steps, based on the estimated position, orientation, and size of the vehicles. In studies by Hu et al. [8.5-36], [8.5-37] motion patterns were learned by neural networks, and the probability of accidents was calculated for partial trajectories obtained by 3D model tracking of vehicles.

Non-vision-based techniques rely on other sensors for vehicle detection since automatic accident detection from videos is very complicated. Harlow and Wang [8.5-38] used acoustic signals to automatically detect accidents by creating a database from traffic features and accident sounds. In a study by Streib et. al. [8.5-39] LIDAR raw data was used to detect vehicles, and the severity of collisions was detected using a 3D model estimation of the target by an extended Kalman filter. Salim et al. [8.5-40]–[8.5-42] used a simulation environment. So, they did not need to address tracking problems. In their work, collision patterns were stored in a knowledge base, and they were populated by means of data mining algorithms.

Vehicle-pedestrian accidents mostly used research that was not vision-based, relying instead on real crash data sets and police reports. Since real datasets were used, statistical inferences were more accurate and valuable. Finding reasons for the accidents [8.5-43] [8.5-44] with regard to the types of vehicles [8.5-45], time, location, and injury [8.5-46] were common subjects for these intersection studies. Crash data sets were used to build a model based on pedestrian intersection safety indices (PED ISI), used to determine the safety index score for a single pedestrian crossing. The model is defined as:

$$PED\ ISI = 2.372 - 1.867(Sl) - 1.807(St) + 0.335(Tl) + 0.018(Sp) + 0.238(Cm) + 0.006(Ma)(S)$$

Where Sl , St and Cm are binary values indicating areas that are signal controlled, having stop signs, and predominantly commercial. Tl is the number of through lanes, Sp is the 85% speed of the street being crossed, and Ma is the main street traffic volume.

TABLE III: Conflict-based safety analysis at intersections

| Study | Data Collection | Goal | Classification, Inference or Approach | Interaction Type |
|--|--|--|---|--------------------|
| Chan and Marco, 2004 [8.5-10] | Recorded video, radar | Traffic monitoring, detecting a red light violation | Estimated the distribution of safety measurements such as DTI versus TTI | vehicle-vehicle |
| Chan and Bougler, 2005 [8.5-25] | Recorded video, instrumented vehicle, radar, loop detector | Assessed conflicts by cooperative roadside and vehicle-based data collection | Estimated the distribution of safety measurements, such as TTC, extracting steering wheels and angles. | vehicle-vehicle |
| Saunier and Sayed, 2006 [8.5-28] | Recorded video | Traffic conflict detection | Using HMM for clustering trajectories of traffic conflicts | vehicle-vehicle |
| Puan and Ismail, 2010 [8.5-29] | Recorded video | Traffic conflict at dilemma zone | Manual video observations; estimated the distribution of abrupt stops, accelerate through amber, running red light; χ^2 test | vehicle-vehicle |
| Ismail et al., 2010 [8.5-12], [8.5-13] | Recorded video | Assessed conflicts | Optical flow tracking, classification of pedestrians and vehicles by speed and trajectory prototypes. | vehicle-pedestrian |
| Su et al., 2008 [8.5-30] | Recorded video | Conflict analysis for exclusive right turns | Manual video observations; conflict was defined as vehicle stoppage or deceleration due to passing pedestrians or bikes. | vehicle-pedestrian |
| Alhajyaseen et al., 2012 [8.5-6] | Recorded video | Conflict analysis with left turner vehicles | Manual video observations; estimated vehicle speed profiles, PET | vehicle-pedestrian |
| Sayed et al., 2012 [8.5-6] | Recorded video | Rear-end and merging conflicts | Optical flow tracking; estimated distribution of TTC and the severity index. | vehicle-pedestrian |
| Qi and Yuan, 2012 [8.5-27] | Recorded video, Survey forms | Pedestrian safety with permissive left-turning vehicles | Poisson regression models; conflicts between pedestrians and left turning/ opposite through vehicles. | vehicle-pedestrian |

TABLE IV: Accident-based safety analysis at intersections

| Study | Data Collection | Goal | Classification, Inference or Approach | Interaction Type |
|--------------------------------------|---------------------------|---|--|--------------------|
| Atev et al., 2005 [8.5-34], [8.5-35] | Recorded video | Collision prediction | Position and 3D model | vehicle-vehicle |
| Kamijo et al., 2000 [8.5-31] | Recorded video | Accident detection and occlusion handling | Spatio-temporal Markov random field and HMM classifier | vehicle-vehicle |
| Ki and Lee, 2007 [8.5-33] | Recorded video | Accident detection and reporting model | Extracted features with a predefined threshold value | vehicle-vehicle |
| Salim et al., 2007 [8.5-40][8.5-42] | Simulation environment | Collision detection | Data mining | vehicle-vehicle |
| Harlow and Wang, 2001 [8.5-38] | Acoustic signals | Accident detection | Feed forward neural network | vehicle-vehicle |
| Akoz and Karsligil, 2011 [8.5-32] | Recorded video | Accident detection | Linear regression | vehicle-vehicle |
| Streib et al., 2008 [8.5-39] | LIDAR | Imminent collision assessment | Unscented Kalman filter | vehicle-vehicle |
| Lee, 2005 [8.5-43] | Crash dataset | Analysis of vehicle-pedestrian crashes | Developed two types of models to analyze frequency and injury severity of pedestrian crashes | vehicle-pedestrian |
| Alghamdi, 2002 [8.5-45] | Crash dataset | Association analysis between crash severity and such variables as age, gender and nationality | Chi-square and odd ratio techniques | vehicle-pedestrian |
| Preusser et al., 2003 [8.5-44] | Crash dataset | Extracted crash type versus culpability pedestrians and drivers | Extracting information from crash datasets reported by the police | vehicle-pedestrian |
| Cinnamon et al., 2011 [8.5-46] | Pedestrian injury dataset | Association between violations and collisions | Manual observation | vehicle-pedestrian |
| Zeeger et al., 2007 [8.5-47] | Recorded video | Developed an index to prioritize crosswalks | Manual observation | vehicle-pedestrian |

8.6 Safety Analysis Studies:

Khajonsak and Sivaramakrishnan [8.6-1] developed macroscopic, planning-level models for pedestrian safety. The proposed model captured the effects of several socioeconomic, transportation, land use, and contextual variables. Results indicated locations with larger volumes of conflicting vehicular and pedestrian movements to be of higher risk for pedestrian crashes. John A. Molino et. al. [8.6-2] presented a metric for measuring pedestrian and bicycle exposure to risk (exposure data). The proposed exposure metric based on the facilities at intersections, midblock road segments, driveways, alleys, parking lots, parking garages, school areas, and areas with playing, dashing, and working in the roadway. Taha Saleem et. al. [8.6-3] study developed crash prediction models from simulated peak hour conflicts for a group of urban four-legged signalized intersections and evaluated their predictive capabilities. The model was simulated using VISSIM and Paramics. The predictive ability of the models for intersections with various ranges of average annual daily traffic and with various combinations of left- and right-turn lanes was assessed. Juan C. Medina et. al. [8.6-4] explored the use of three well-known methods for multi-attribute decision making (MADM) to select optimal traffic signal control parameters in a multimodal scenario at pedestrian crossing intersections. Luís Vasconcelos et. al. [8.6-5] implemented surrogate safety assessment model (SSAM) is a software application that reads trajectory files generated by microscopic simulation programs and calculates surrogate measures of safety. SSAM results with conflicts observed and validated on site in four real intersections. Robert J. Schneider [8.6-6] study presents a methodology for estimating weekly pedestrian intersection crossing volumes based on 2-h manual counts. Results of this study demonstrate how pedestrian volumes can be routinely integrated into transportation safety and planning projects. Robert J. Schneider also proposed a simple pilot model of pedestrian intersection crossing volumes. Mohamed H. Zaki et. al. [8.6-7] presented the use of computer vision techniques for the automated collection of cyclist data. Cyclist tracks obtained from video analysis were used to perform screen line counts as well as cyclist speed measurements. Further analysis was conducted on the mean speed of cyclists with regard to several factors (e.g., travel path, helmet use, group size).

8.7 Safety Analysis Simulations:

Gang Ren et. al. [8.7-1] propose a simulation model capable of estimating crossing time for various levels of pedestrian demand. The observation field data extracted from the video record validated the model's ability to estimate average crossing speed. It also found that pedestrian crossing time and speed are correlated to pedestrian demand. Dang Minh Tan et. al. [8.7-2] developed a microscopic simulation model to assess the safety of signalized intersections. The proposed simulation model integrates many key behavioral models of road users, such as the stop-go decision at the onset of a yellow light, turning paths, turning speeds, start-up response time, and pedestrian gap acceptance models. The validation results show that the simulation model reasonably represents the occurrence of conflicts at signalized intersections, which proves that the proposed model can be a reliable approach to safety assessment. Ahmed Abdelghany et. al. [8.7-3] developed PEDSTREAM, a mesoscopic simulation-based dynamic trip assignment model for large-scale pedestrian networks. The model can represent temporo-spatial distribution of pedestrians and associated service levels over the network

and can predict pedestrian responses to changes in design, operational conditions, and crowd management strategies.

8.8 Pedestrian-Vehicle Conflict Frameworks and Studies

Tara Tolford et. al. [8.8-1] proposed a framework for a comprehensive, low-cost pedestrian safety analysis incorporating multiple data sources and analysis techniques. Their methodology includes an evaluation of available crash records, an audit of current pedestrian facilities, collection of pedestrian count data, and an assessment of relevant contextual factors. Together, these elements provide a holistic view of pedestrian safety and comfort, informing needed interventions. Karim Ismail et. al. [8.8-2] developed an automated video analysis system is presented that can (a) detect and track road users in a traffic scene and classify them as pedestrians or motorized road users, (b) identify important events that may lead to collisions, and (c) calculate several severity conflict indicators. The system seeks to classify important events and conflicts automatically but can also be used to summarize large amounts of data that can be further reviewed by safety experts. Mohamed H. Zaki and Tarek Sayed [8.8-3] developed an automated system for identifying pedestrian crossing nonconformance to traffic regulations by using pattern matching was developed and tested. Detecting both spatial and temporal violations, with the detection rate for violations being more than 84% correct. Paul St-Aubin et. al. [8.8-4] developed a methodology for detailed analysis of driving behavior, trajectory interpretation, and conflict measures in modern roundabouts, based on video data extracted by means of computer vision. The analysis explores the methods used to prepare microscopic speed maps, compiled speed profiles, lane-change counts, and gap time measures. Yan Yang and Jian Sun [8.8-5] proposed a model for pedestrian red-time crossing choice was proposed on the basis of integrated field observations and questionnaire data. The model was compared with models based on either observational data alone or questionnaire data alone and proved to be well fit and to yield better prediction accuracy. Ioannis Kaparias et. al. [8.8-6] developed pedestrian-vehicle conflict analysis (PVCA) method. Their work presents a systematic process for identifying conflict occurrences on the one hand and the full quantification of the conflict severity grading process on the other. Stewart Jackson et. al. [8.8-7] presents a scalable, discreet, mobile video camera system that takes elevated video data of roadway locations for traffic safety analysis. The video is used to extract microscopic traffic parameters that include road user trajectories, lane changes, and speeds. Collected video data are processed with an open source automatic tracking tool. Trajectories can then be used to analyze road user behavior for specific locations (intersections or highway sections) or to evaluate the safety effectiveness of a treatment. Mohamed H. Zaki et. al. [8.8-8] automated safety diagnosis of pedestrian crossing safety issues by using computer vision techniques. They attempt to extract conflict indicators and detect violations from video sequences in a fully automated way. The system includes a permanent database for traffic information that can be beneficial for a sound safety diagnosis as well as for developing safety countermeasures.

Mohamed H. Zaki et. al. [8.8-9] propose a automated identification of pedestrian crossing violations with computer vision techniques. Two types of violations are considered. The first is spatial violations:

pedestrians cross an intersection in non-designated crossing regions. The second is temporal violations: pedestrians cross an intersection during an improper signal phase. The results show satisfactory accuracy in the detection of spatial and temporal violations, with an approximately 90% correct violation detection rate having been achieved in case studies. Jeffrey Shelton et. al. [8.8-10] explored new methods to supplement the Road Safety Audit process. The study used visualization tools to assess the performance of each proposed improvement strategy by conducting a more thorough comprehensive safety study with multi-resolution modeling methods in situations when suggested countermeasures would almost certainly redistribute traffic to alternative routes. Katayoun Salamati et. al. [8.8-11] work relates pedestrian crossing decisions to advanced measurements of vehicle dynamics to estimate lane-by-lane conflicts and identifies the grade of conflict on the basis of a five-criterion rating scale. The conflict-based assessment of pedestrian safety (CAPS) framework was applied to a study of crossings by blind pedestrians at a multilane roundabout. The resulting risk scores were calibrated from the actual orientation and mobility interventions observed during the study. Tarek Sayed et. al. [8.8-12] implemented an automated conflict detection with data extracted from video sensors on right-turn safety improvement was implemented at an intersection. The video data were analyzed and traffic conflicts were measured with an automated traffic safety tool. Distributions of the calculated conflict indicators before and after the treatment showed a considerable reduction in the frequency and severity of traffic conflicts. Karim Ismail et. al. [8.8-13] proposes and compares two approaches to detect vehicular spatial violations. The approaches are (a) k-means clustering and (b) pattern matching with use of the longest common subsequence (LCSS) similarity measure. The purpose of this study was to learn what constituted normal movement patterns and to interpret any discrepancy between these patterns and observed tracks as an indication of a traffic violation. Karim Ismail et. al. [8.8-14] also measure the severity of traffic events. The first set of conflict indicators required the presence of a collision course common to the interacting road users. The second set measured severity in mere temporal proximity between road users. The study proposes a methodology with which to aggregate the event-level measurements of conflict indicators into a safety index.

8.9 Safety Analysis Tools:

Below is a brief summary of existing safety analysis tools specifically addressing pedestrian levels of services and pedestrian safety indexes at intersections.

Pedestrian and Bicycle Crash Analysis Tool (PBCAT) [8.9-1]

PBCAT is a software application designed to assist State and local pedestrian and bicycle coordinators, planners, and engineers address pedestrian and bicyclist crash problems. PBCAT helps users create a database of details associated with crashes between motor vehicles and pedestrians or bicyclists, analyze the data, produce reports, and select countermeasures to address problems identified.

Pedestrian Safety Guide and Countermeasure Selection System (PEDSAFE) [8.9-2]

PEDSAFE provides practitioners with the latest information available for improving the safety and mobility of those who walk. This online tool gives users a list of possible engineering, education,

and/or enforcement treatments to improve pedestrian safety and/or mobility based on user input about a specific location.

Bicycle Countermeasure Selection System (BIKESAFE) [8.9-3]

BIKESAFE provides practitioners with the latest information available for improving the safety and mobility of those who bicycle. BIKESAFE's resources include an overview of bicycling in today's transportation system and information about bicycle crash factors and analysis and selecting and implementing bicycling improvements. BIKESAFE's tools allow users to select appropriate countermeasures or treatments to address specific bicycling objectives or crash problems.

Pedestrian and Bicycle Geographic Information System (GIS) Safety Tools [8.9-4]

GIS software turns statistical data (such as accidents) and geographic data (such as roads and crash locations) into meaningful information for spatial analysis and mapping. In this suite of tools, GIS-based analytical techniques have been applied to a series of pedestrian and bicycle safety issues, including safe routes for walking to school, selection of streets for bicycle routes, and high pedestrian crash zones. Users downloading these tools must meet minimum GIS software requirements.

LOS+ Multi-Modal Roadway Analysis Tool [8.9-5]

LOS+ is a multi-modal level of service roadway analysis tool that was developed by Fehr & Peers. LOS+ is capable of analyzing auto, pedestrian, bicycle, and transit level of service for urban streets. LOS+ was developed as a quick-response and lower-cost alternative to other multi-modal analysis software.

9. FUTURE PLAN

The process involved in automatic extraction of pedestrian and vehicle flow parameters is shown in Figure 3 describes the Pedestrian Analysis (PA) sub-system, Vehicle Analysis (VA) sub-system and the Pedestrian-Vehicle Conflict Analysis sub-systems. The macroscopic pedestrian data extracted by the PA sub-system include fundamental flow characteristics like pedestrian count, pedestrian flow (in both directions), average speed of pedestrians, and average time for pedestrians to cross the intersection. The research team will implement a robust and accurate PA sub-system that is location invariant. Efficient algorithms will be developed for pedestrian detection and tracking.

The Vehicle Analysis subsystem performs vehicle detection and tracking on video frames to extract vehicle flow characteristics. The VA system analyses the video sequence of the vehicles approaching the pedestrian crossing. The vehicle flow parameters that will be automatically extracted by the VA system include: vehicle volume, average speed of the vehicles, speed of individual vehicles, stopping distance of the vehicles from the pedestrian crossing, etc.

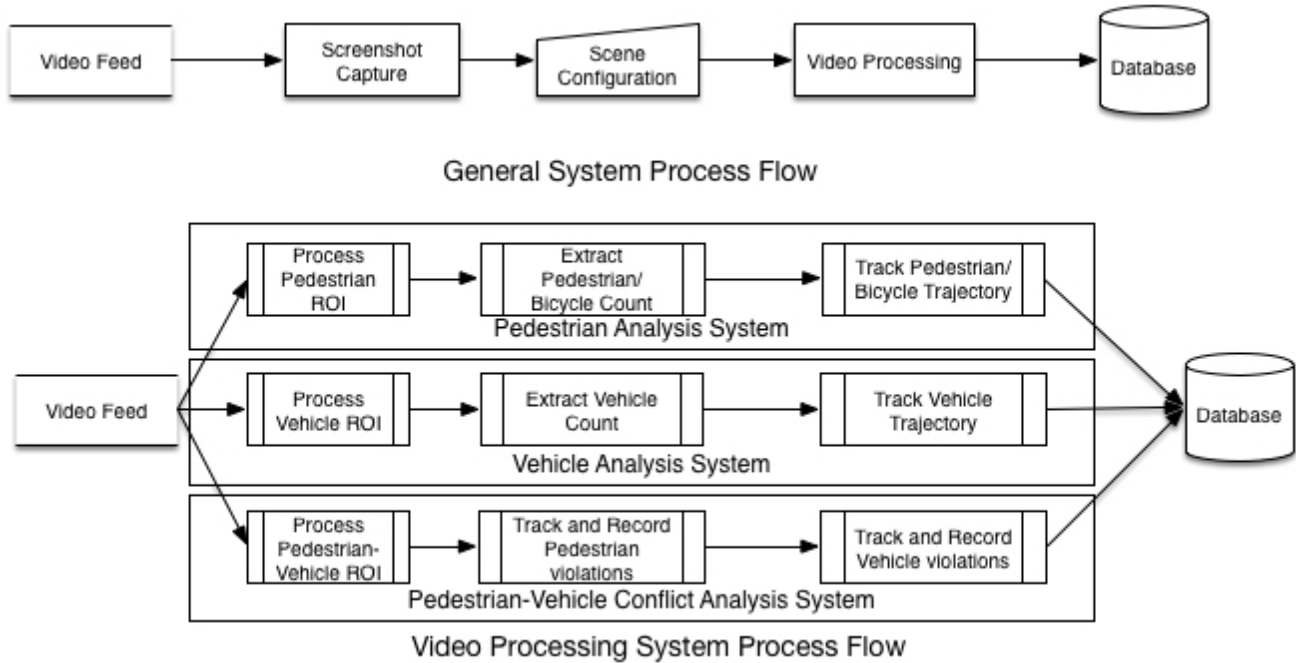


Figure 3: Video Processing System Process Flow

In both, PA and VA sub-systems, calibration of the system is required to obtain actual spatial and temporal parameters from the data extracted by the image processing algorithms. Calibrating the PA and VA sub-systems using reference lines and regions on the location does this. This process is carried out during the configuration of the system. Configuration of the system, maps the coordinates of the image to actual real-world dimensions. A sample configuration scenario is shown in Figure 4. The automated data extracted by the PA and VA sub-systems are now used in the detection and recording of pedestrian-vehicle conflicts.

The purpose of the Pedestrian-Vehicle conflicts system is to automate the pedestrian-vehicle conflict detection, classification and determination of intersection safety LOS. The proposed system will model and examine the tracks of pedestrians and vehicles that are obtained by PA-VA sub-system. So we can determine the conflict point, which can be defined as point that they collide if they continue with their current speeds. This is based on definition of TTC (Time to Collision). Low TTC values indicate severity of conflicts and we will estimate the TTC distribution and the heat map showing highly severe conflict locations. Figure 5, shows the query pedestrian-vehicle conflict. Once the conflict is determined based on image processing/analysis techniques, the pedestrian-vehicle conflict analysis task stores spatial and temporal data of the pedestrian and vehicle trajectory and flow parameters from the previous task (PA and VA system).

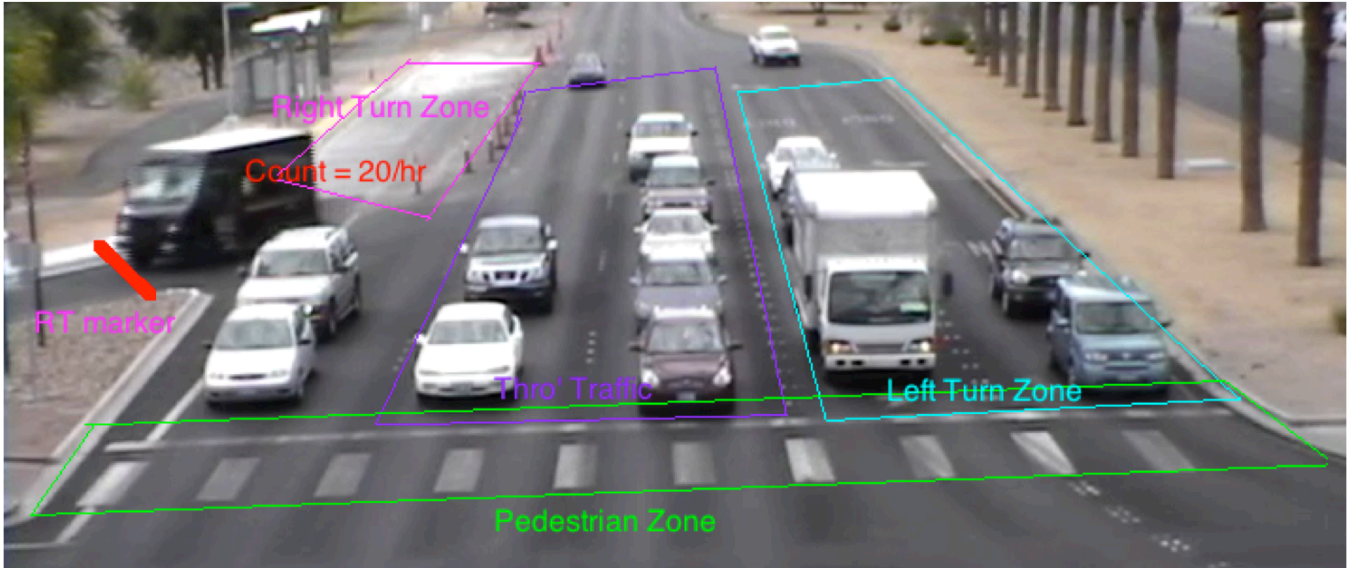
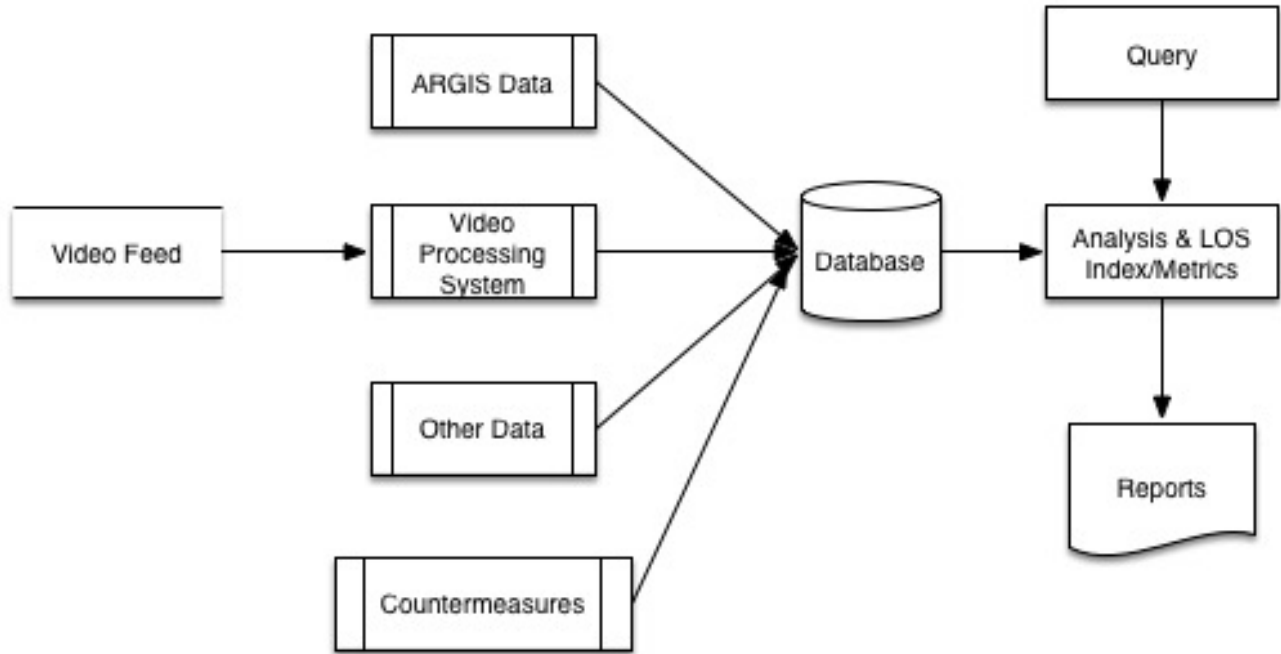


Figure 4: Intersection Configuration file



Query System Process Flow

Figure 5: Query System for Intersection Safety Analysis

10. CONCLUSION

This sections summaries the lessons learned through literature survey conducted by various groups and future tasks to be pursued during the next quarter of this project. A comprehensive literature review of pedestrian detection and tracking methods using in video processing and pedestrian count and analysis studies conducted in the field of Transportation engineering was also reviewed. We have identified and started implementation of pedestrian detection and tracking method (multi-feature multi-channel feature extraction). Pedestrian flow characteristics like pedestrian count, pedestrian volume, crossing speeds and trajectories will be extracted and recorded. Comprehensive bicycle detection methods in image processing journals and articles have been explored. Not much work on automated bicycle detection has been reported in Transportation Engineering related journals. The research team will deploy bicycle detection based on SVM classifier on robust HOG features followed by MCMC particle tracker. This method is feasible for bicycle detection at intersection. Bicycle flow characteristics like count, volume, crossing speeds and trajectories will be extracted and recorded. Also, extensive research on pedestrian safety analysis, pedestrian-vehicle conflict analysis systems, and pedestrian safety simulation models has been completed. A large part of the work deals with manual or automated data collection of pedestrian or vehicle flow characteristics to evaluate the safety metrics for a specific implementation of level of service. Safety analysis tools consider manual data entry that include pedestrian and vehicle volumes, and crash data. Through literature surveys we have identified the data requirements for our proposed automated intersection safety analysis systems. Currently, we are in the process of implementing various pedestrian, vehicle and conflict detection algorithms on video feeds.

Reference:

SECTION 8.1

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